Cortical Networks Research at IBM

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Neural modeling: capabilities and desired data

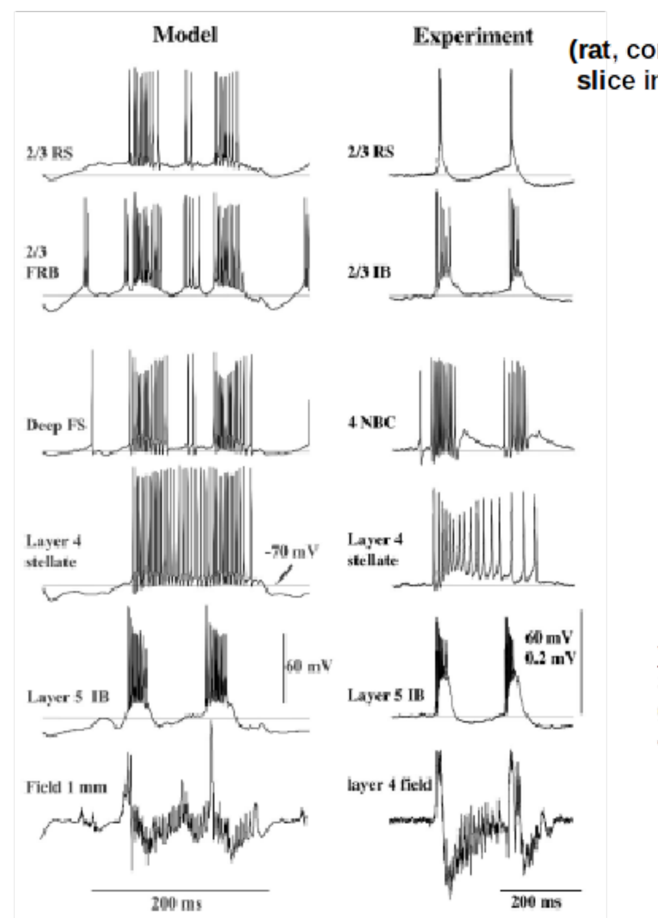
1. Detailed mesoscopic model of thalamocortical interactions

- A detailed model of a single cortical column was developed [R. Traub et al, J. Neurophysiol, 2005]. The model has been successful in explaining and predicting cortical dynamics such as oscillations and seizures .

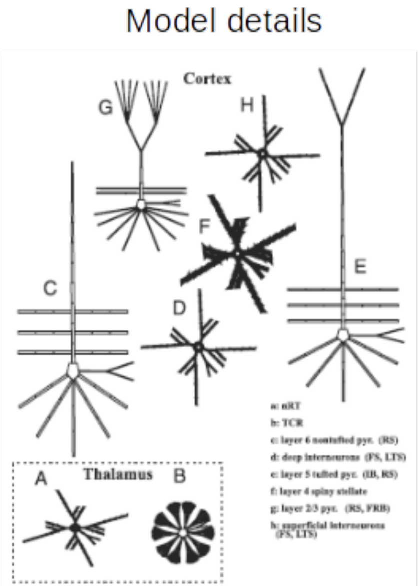
- Realistic multi-column model is being developed.

- **Data needed:** Recording in multiple cortical regions is highly desirable. Connectomics data, especially those related to connected brain regions can be used to constrain the models.

Single-column model can predict seizure activity in rat brain slices



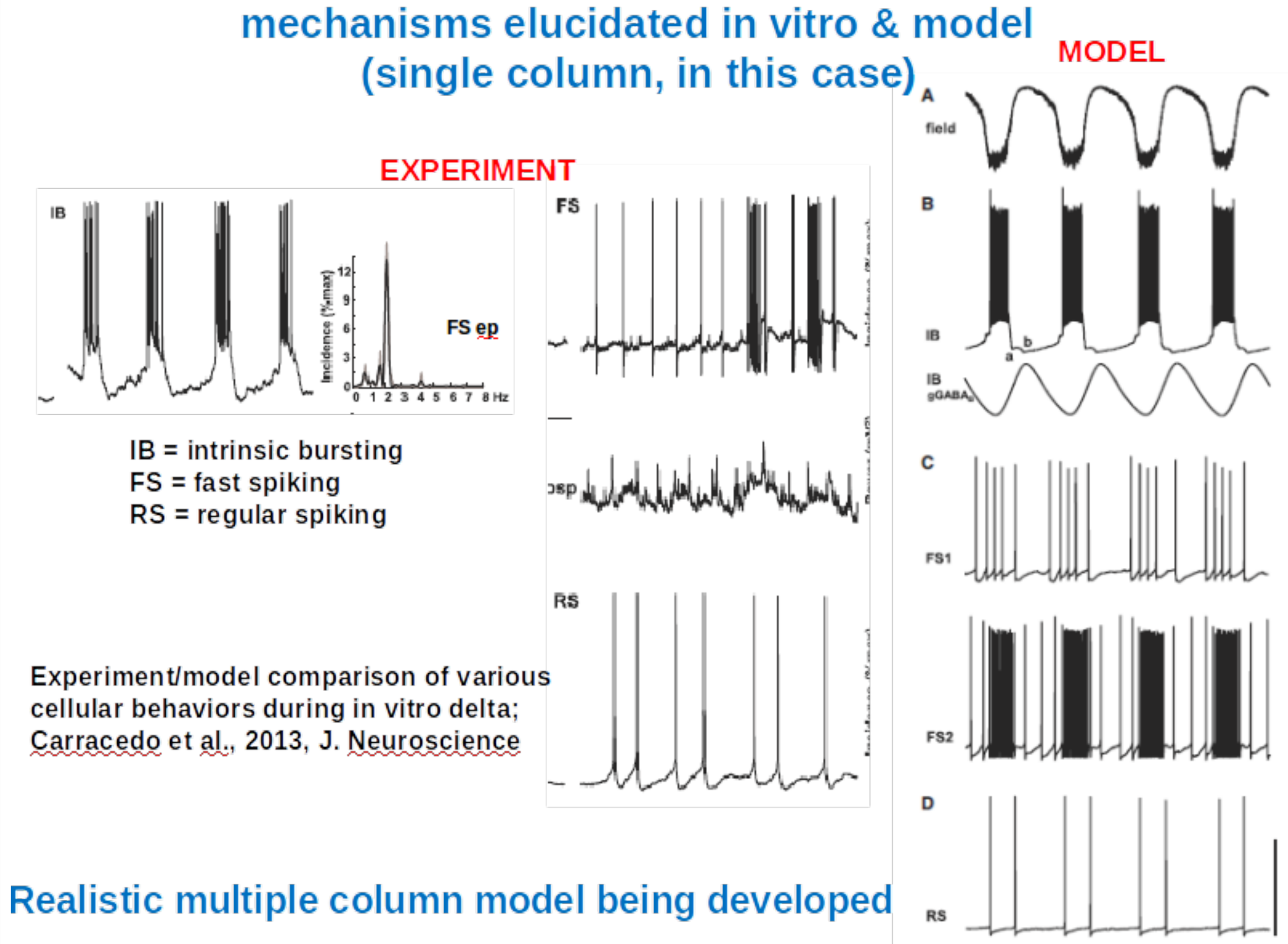
Model details



Traub, R.D., Contreras, D.,...Whittington, M.A. (2005) Single-column thalamocortical network model exhibiting gamma oscillations, sleep spindles and epileptogenic bursts. J. Neurophysiol. 93: 2194-2232.

RS = regular spiking
FRB = fast rhythmic bursting
IB = intrinsic bursting
FS = fast spiking
NBC = nested basket cell

Another example of a behaviorally relevant cortical oscillation mechanisms elucidated in vitro & model (single column, in this case)



IB = intrinsic bursting
FS = fast spiking
RS = regular spiking

Experiment/model comparison of various cellular behaviors during in vitro delta; Carracedo et al., 2013, J. Neuroscience

Realistic multiple column model being developed

2. Neural network models linking neural activity and behavior

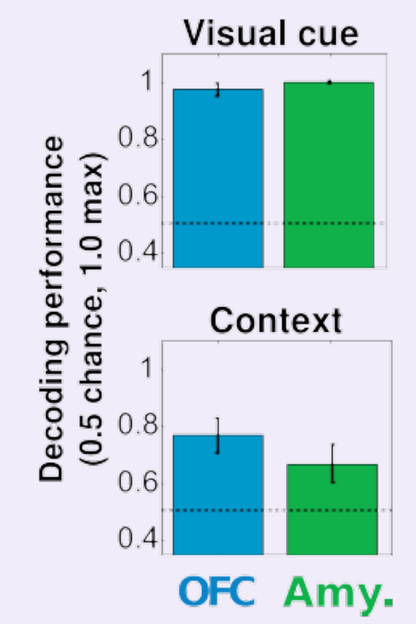
- We developed a neural network models that extract the hidden context variables and allow for adaptive behavior in uncertain environments [M. Rigotti et al, NeuroImage, 2010].

- We are studying the neural basis for context-dependent data representation and decision making, and how these ideas may be used in ML.

- **Data needed:** simultaneous measuring context-dependent behavior performance and neural activity in higher animals. Connectomics can be used to constrain the models.

Feature extraction for context-dependent recognition and Reinforcement Learning in partially observable environments

- **Behavior** of macaque monkeys trained on a context-dependent discrimination of visual cues displays **rapid adaptation** *to changing context*
- Analysis of ***in-vivo* electrophysiology** data shows encoding in amygdala and OFC of both: *observable visual cues* and *hidden contextual information.*



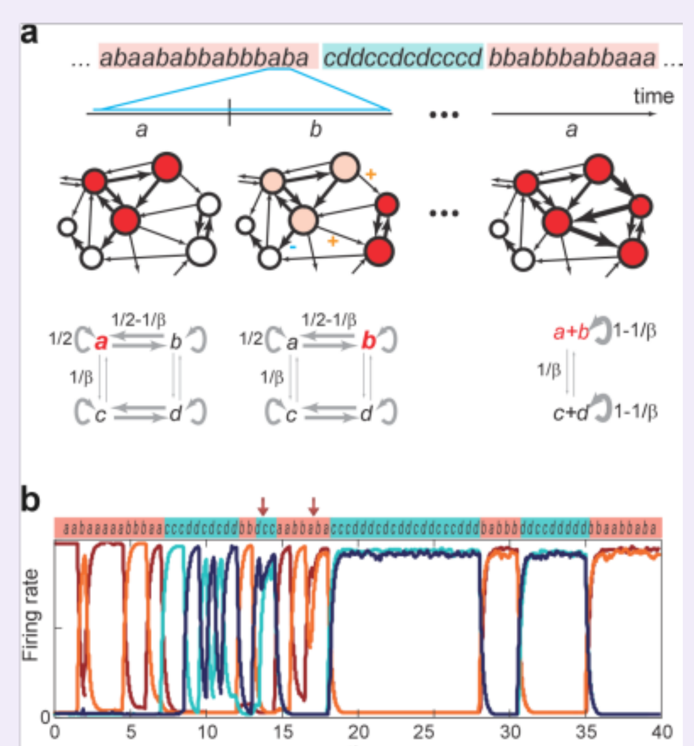
[joint work with C.D. Salzman at Columbia University]

Conclusions:

1) The primate brains *extracts* and *encodes* **hidden contextual variables** of the environment, besides visible ones
2) Information is **distributed across area**: cortex (OFC) and subcortical regions (Amygdala)
3) This information is crucial to perform **rapid adjustment to changing context**: when context encoding is weak, behavior is impaired (not shown)

Unsupervised feature extraction for context-dependent Reinforcement Learning (RL)

- We developed a **neural network model** that *extracts the hidden context variables* through **unsupervised Hebbian learning**
- This hidden information can be used to improve current RL methods in partially observable environments
- Model predictions are compatible with behavior and electrophysiology observation



Neural network observes sequences of cues and creates **attractor states** that encode hidden context variables [Rigotti et al. NeuroImage, 2010]

Conclusions:

1) Computational neuroscience models can be used to bridge **neural activity** and **behavior**
2) They also provide constraint for detailed cortical circuit models and
3) Reveal computational principles to exploit in new ML algorithms

3. Modeling of global architecture for behaviorally-driven perception

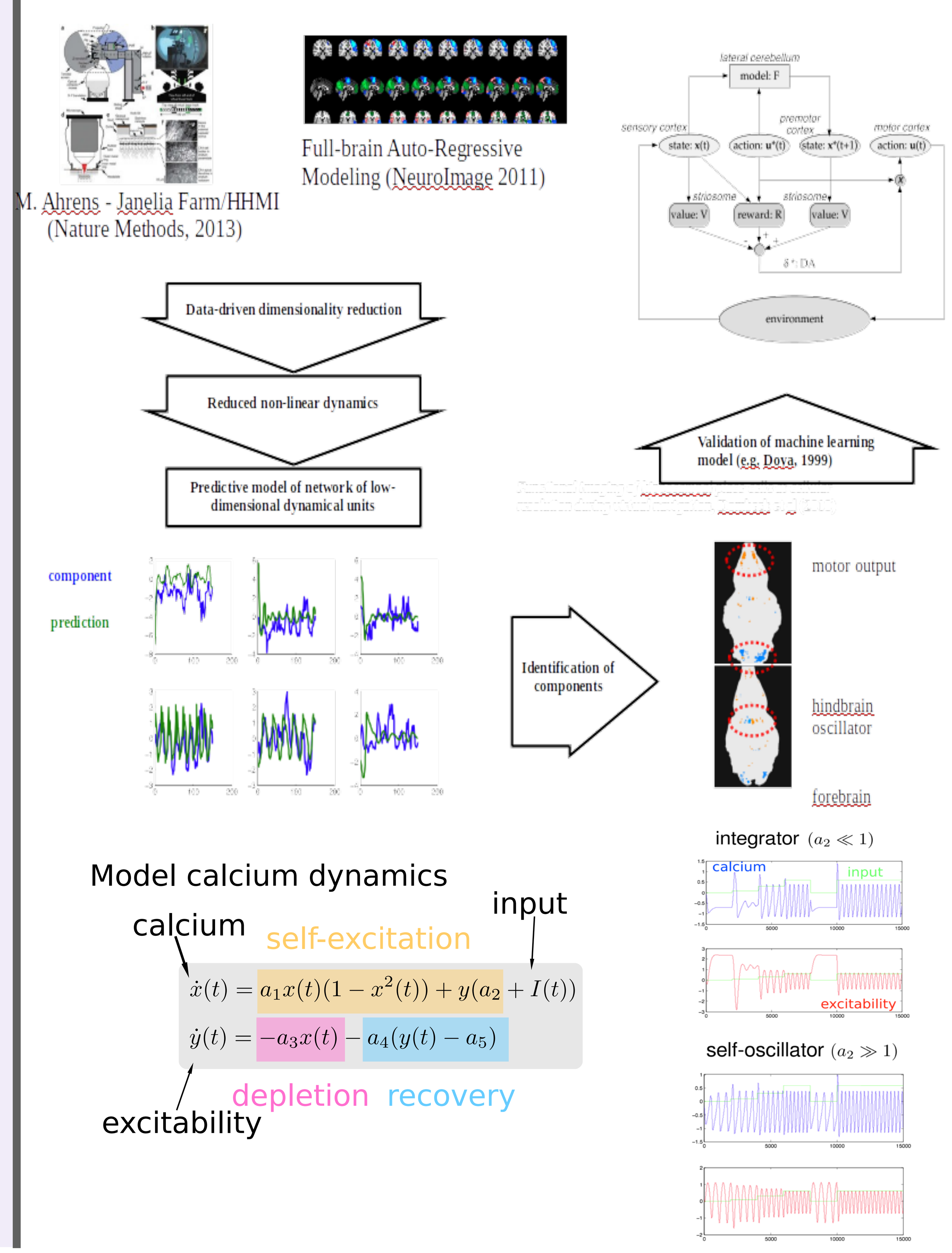
- Perceptual learning is achieved through action-perception loops.

- Cortical architectures are intimately embedded in anatomical reentrant patterns dominated by behavioral functionality, i.e. cortico-thalamic-basal loops.

- We have implemented linear and non-linear predictive models of large-scale imaging data including fMRI and calcium imaging (Neuroimage 2011, IEEE 2011, JMLR 2013) in HPC (Blue Gene)

- We are studying how the predictive dynamical components can be interpreted in a machine learning framework.

- **Data needed:** Functional: large-scale functional data: calcium imaging, high-resolution fMRI, multi-area electrode array recordings.
Anatomical: DTI, axonal tracing and EM reconstructions that can explicitly identify inter- and intra-area connectivity.



$$\dot{x}(t) = a_1 x(t)(1 - x^2(t)) + y(a_2 + I(t))$$
$$\dot{y}(t) = -a_3 x(t) - a_4(y(t) - a_5)$$

Machine Learning

IBM Research Expertise in Machine Learning: Neuroscience-related Algorithmic Innovations and Applications

- **Infomax** (Ralph Linsker): self-organizing principle for cortical learning
- **Reinforcement Learning** (RL)
  - Gerald Tesauro: developed TD-Gammon (self-teaching backgammon program) – first significant application of RL
  - Additional applications in e-commerce agents, self-managing computing systems, and Watson's Jeopardy! game-playing strategy
  - Naoki Abe et al.: successful deployed applications of RL for sequential targeted marketing; optimizing debt collections
- **ML for Neuroimaging data** (Guillermo Cecchi & Irina Rish): fMRI Analysis; Schizophrenia Classification
- **Deep Neural Network Learning:** Large-scale applications in Speech Recognition (Brian Kingsbury, Bhuvana Ramabhadran et al.) and in Image / Video classification (Liang-liang Cao)

Other IBM Research Expertise in Machine Learning

- **Active Learning**
- **Graphical Models / Bayes Nets**
- **Manifold Learning**
- **Collaborative Filtering**
- **Sparsity Constraints**
- **Latent Topic Modelling**
- **Relational Learning**
- **Spatio-Temporal Predictive Models**
- **NIMBLE Platform:** enables rapid parallel implementation of ML algorithms using MapReduce/Hadoop

Large scale circuit models

Ultrascalable solution to cortical Microcircuit and connectomic-based simulation

TISSUE BOUNDARY CONSTRAINTS-BASED STRUCTURAL MODEL

MODELING APPROACH:

Develop tissue meshes based on histology, MRI

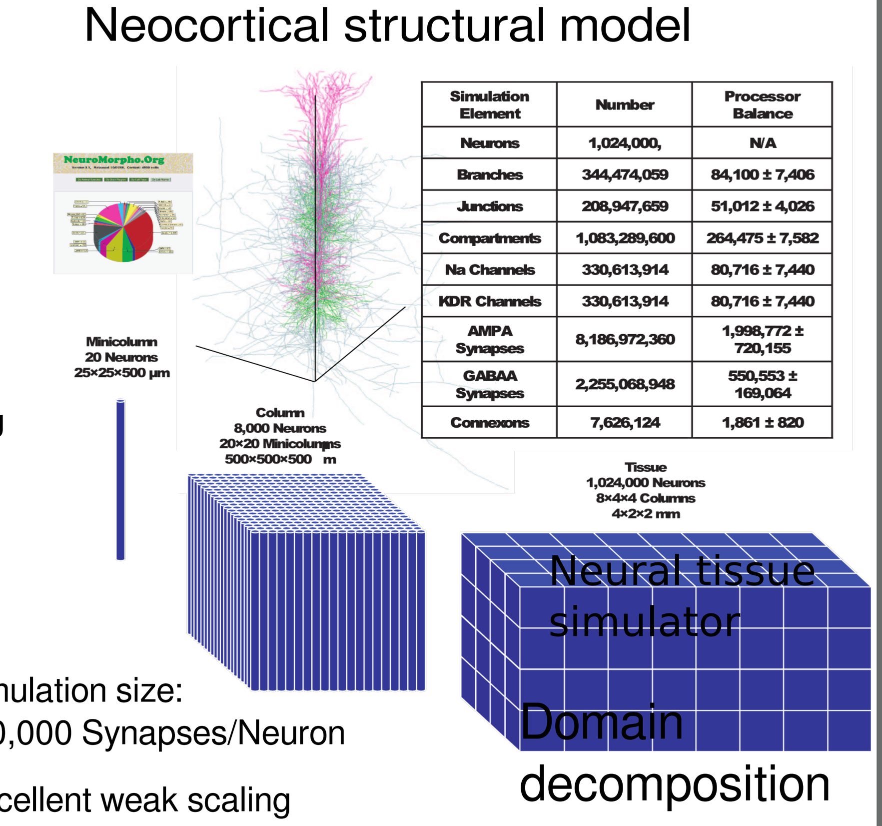
Growth algorithm inserts neurons within mesh

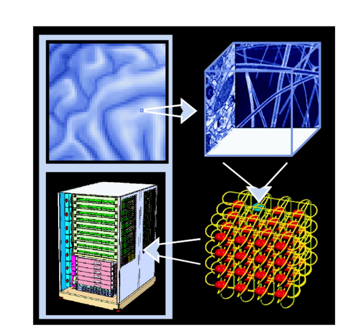
Constrain neuronal fiber growth using mesh repulsion representing boundaries

Model tract waypoints using DTI, transformations into Poisson problems of charge, conductivity, gradients.

Constrain axonal growth

Neocortical structural model





Simulation size:
~10,000 Synapses/Neuron

Excellent weak scaling demonstrated on BlueGene/P up to 5000 nodes:
~250 Neurons/Processor